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A Modified Generalized Memory Polynomial Model for RF Power Amplifiers

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Abstract—A modified generalized memory polynomial model (MGMP) is proposed for RF power amplifiers (PAs). The MGMP model is derived by applying complexity-reduced technique to the generalized memory polynomial model (GMP), and the least square (LS) algorithm is used for coefficient extraction. The proposed MGMP model is assessed using a GaN Class-F PA driven by two modulated signals (a WCDMA 1001 signal and a single carrier 16QAM signal with 20 MHz bandwidth). The experimental results demonstrate that the MGMP model outperforms the memory polynomial (MP) model and the generalized memory polynomial (GMP) model. Compared with MP model, the MGMP model shows a normalized mean square error (NMSE) improvement of 2.13 dB in forward modeling, average adjacent channel power ratio (ACPR) improvement of 2.62/2.11 dB in the DPD application with almost identical number of model coefficients. In contrast with the GMP model, the MGMP model can achieve comparable forward modeling and linearization performance results, but reduces approximately 40% of coefficients.

1. INTRODUCTION

Power amplifiers (PAs) are one of the most indispensable components in modern communication system and inherently nonlinear. When PAs are applied into wireless communication system, it creates fearful in-band distortion and spectral regrowth. To compensate and cancel these nonlinear effects, it needs behavioral modeling accurately for power amplifiers (PAs) in practical applications.

Accurate modeling offers effective prediction of PA nonlinearity and the inverse model as a digital predistorter is developed for the linearization [1–3]. The key goal of digital predistorter is to find a good model to approximate the inverse of the PA nonlinearity. The memory polynomial (MP) model [4, 5] is widely used for behavioral modeling of the PA in practical application. However, adding contiguous items about PA to the MP model can further improve the accuracy of the MP model. Although the generalized memory polynomial (GMP) [6] model including the cross-band modulation terms is proposed for its high accuracy, a high model complexity is unavoidable when the values of memory depth and nonlinearity order are high. This is because all memory depths have the same nonlinearity order as many predistortion models [7–10].

In this paper, a modified GMP (MGMP) model is presented to reduce the estimated number of modeling coefficients of GMP model. The experimental results including forward modeling results and linearization performance fully illustrate the MGMP model, and the GMP model can improve the modeling performance in comparison with the MP model. However, in terms of the MGMP model and GMP model, the MGMP model can achieve comparable modeling accuracy in comparison with the GMP model but reduces approximately 40% model coefficients. Since each memory depth has a different maximum nonlinearity order, the number of model coefficients is significantly decreased compared to

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the GMP model. GMP, MGMP models are detailed in Section 2. In Section 3, the forward modeling results and linearization performance are reported. Finally, a conclusion is given in Section 4.

2. MODEL DESCRIPTION

2.1. GMP Model

The GMP model [6] is an evolution of the MP model. Based on the MP model [5], it adds to other contiguous items about PA, namely cross terms. Getting rid of redundant items, the mathematical of the GMP model can be expressed as:

$$\begin{aligned} y_{GMP}(n) \;=\; & \sum_{\substack{k=1 \\ k\text{-}odd}}^{K_a} \sum_{m=0}^{M_a} a_{km} x(n-m) \left| x(n-m) \right|^{k-1} \\ & + \sum_{\substack{k=3 \\ k\text{-}odd}}^{K_b} \sum_{m=0}^{M_b} \sum_{l=1}^{L_b} b_{kml} x(n-m) \left| x(n-m-l) \right|^{k-1} \\ & + \sum_{\substack{k=3 \\ k\text{-}odd}}^{K_c} \sum_{m=0}^{M_c} \sum_{l=1}^{L_c} c_{kml} x(n-m) \left| x(n-m+l) \right|^{k-1} \end{aligned} \tag{1}$$

where $x(n)$ and $y_{GMP}(n)$ are the input and output signals of the GMP model, respectively. K_a, M_a, and a_{km} are the nonlinearity order, memory order and coefficients of the aligned terms between signal and its exponentiated envelope, respectively. K_b, M_b, L_b and b_{kml} are the nonlinearity order, memory depth, lagging cross terms index, and coefficients of the signal and lagging exponentiated envelope terms, respectively. K_c, M_c, L_c and c_{kml} are the nonlinearity order, memory depth, leading cross terms index, and coefficients of the signal and leading exponentiated envelope terms, respectively. The estimated number of the GMP model coefficients is $[(K_a+1)\times(M_a+1)+(K_b-1)\times(M_b+1)\times L_b+(K_c-1)\times(M_c+1)\times L_c]/2$.

2.2. MGMP Model

In formula (1), the maximum nonlinear order is constant for every input of one of the three formulas. It leads to a high model complexity when the values of memory depth and nonlinearity order are high, but the increasing number of model coefficients is not corresponding to the increasing model accuracy. The reduced-complexity technology removes some items which contribute to modeling accuracy rarely. The effects of nonlinear dynamics tend to fade with increasing order in many real PAs [11, 12], and we can attempt to adjust the maximum nonlinearity order of the previous input to decrease the number of coefficients and achieve accurate behavioral model of PAs.

Let K_{as} take the place of K_a , and K_{as} is defined as following:

$$K_{as} = \begin{cases} K_a - 2m, & m < (K_a+1)/2 \\ 1, & m \geq (K_a+1)/2 \end{cases} \tag{2}$$

Likewise, let K_{is} take the place of K_i $(i = b,\ c)$, and K_{is} is expressed as follows:

$$K_{is} = \begin{cases} K_i - 2m, & m < (K_i-1)/2 \\ 3, & m \geq (K_i-1)/2 \end{cases} \tag{3}$$

Then, using K_{as} and K_{is} in the place of K_a and K_i, respectively, Equation (1) becomes:

$$\begin{aligned} y_{MGMP}(n) \;=\; & \sum_{\substack{k=1 \\ k\text{-}odd}}^{K_{as}} \sum_{m=0}^{M_a} a_{km} x(n-m) \left| x(n-m) \right|^{k-1} \\ & + \sum_{\substack{k=3 \\ k\text{-}odd}}^{K_{bs}} \sum_{m=0}^{M_b} \sum_{l=1}^{L_b} b_{kml} x(n-m) \left| x(n-m-l) \right|^{k-1} \end{aligned}$$

$$+\sum_{\substack{k=3\\k\text{-}odd}}^{K_{cs}}\sum_{m=0}^{M_c}\sum_{l=1}^{L_c} c_{kml}x(n-m)\left|x(n-m+l)\right|^{k-1} \tag{4}$$

where $x(n)$ and $y_{MGMP}(n)$ are the input and output signals of the MGMP model, respectively. K_{as}, M_a and a_{km} are the maximum nonlinearity order, maximum memory order and coefficients of the aligned terms between signal and its exponentiated envelope, respectively. K_{bs}, M_b, L_b and b_{kml} are the maximum nonlinearity order, maximum memory depth, lagging cross terms index, and coefficients of the signal and lagging exponentiated envelope terms, respectively. K_{cs}, M_c, L_c and c_{kml} are the maximum nonlinearity order, maximum memory depth, leading cross terms index, and coefficients of the signal and leading exponentiated envelope terms, respectively.

The MGMP model can take three parts into consideration, and the three parts can be written separately as follows:

$$y_{align} = \sum_{\substack{k=1\\k\text{-}odd}}^{K_{as}}\sum_{m=0}^{M_a} a_{km}x(n-m)\left|x(n-m)\right|^{k-1} \tag{5}$$

$$y_{lag} = \sum_{\substack{k=3\\k\text{-}odd}}^{K_{bs}}\sum_{m=0}^{M_b}\sum_{l=1}^{L_b} b_{kml}x(n-m)\left|x(n-m-l)\right|^{k-1} \tag{6}$$

$$y_{lead} = \sum_{\substack{k=3\\k\text{-}odd}}^{K_{cs}}\sum_{m=0}^{M_c}\sum_{l=1}^{L_c} c_{kml}x(n-m)\left|x(n-m+l)\right|^{k-1} \tag{7}$$

The MGMP model can be illustrated as:

$$y_{MGMP} = y_{align} + y_{lag} + y_{lead} \tag{8}$$

The estimated number of model coefficients about y_{align}, y_{lag} and y_{lead} is summarized in Table 1. The total number of the MGMP model coefficients is summation to the number of the estimated coefficients of y_{align}, y_{lag} and y_{lead}.

3. EXPERIMENTAL VALIDATION

To experimentally demonstrate the proposed MGMP model, a high efficiency 20 W GaN Class-F PA (V_{ds} = 28 V, V_{gs} = 5 V) was tested. This PA was operated at 2.65 GHz and excited by a WCDMA 1001 signal (PAPR = 11.08 dB) and a single carrier 16QAM (PAPR = 8.06 dB) signal with 20 MHz bandwidth. Fig. 1 shows the test bench setup.

The experiment test bench consists of a GaN Class-F PA, a vector signal generator (N5182A), a vector signal analyzer (N9030A) and a computer. The digital base band signal was generated in the computer and downloaded into N5182A, which modulated and up-converted the digital base band signal that droved the PA with RF input signals. The RF output of the PA was attenuated and then

Table 1. Number of model coefficients about every part of the MGMP model.

Part	Condition	Number of coefficients
y_{align}	$M_a < (K_a+1)/2)$	$(M_a+1)\times(K_a+1-M_a)/2$
	$M_a \geq (K_a+1)/2$	$(K_a+1)\times(K_a+3)/8+M_a-(K_a-1)/2$
y_{lag}	$M_b < (K_b-1)/2$	$(M_b$+1)×(K_b-1-M_b) × $L_b/2$
	$M_b \geq (K_b-1)/2$	$[(K_b-1)\times(K_b+1)/8+M_b-(K_b-3)/2]\times L_b$
y_{lead}	$M_c < (K_c-1)/2$	$(M_c+1)\times(K_c-1-M_c)\times L_c/2$
	$M_c \geq (K_c-1)/2$	$[(K_c-1)\times(K_c+1)/8+M_c-(K_c-3)/2]\times L_c$

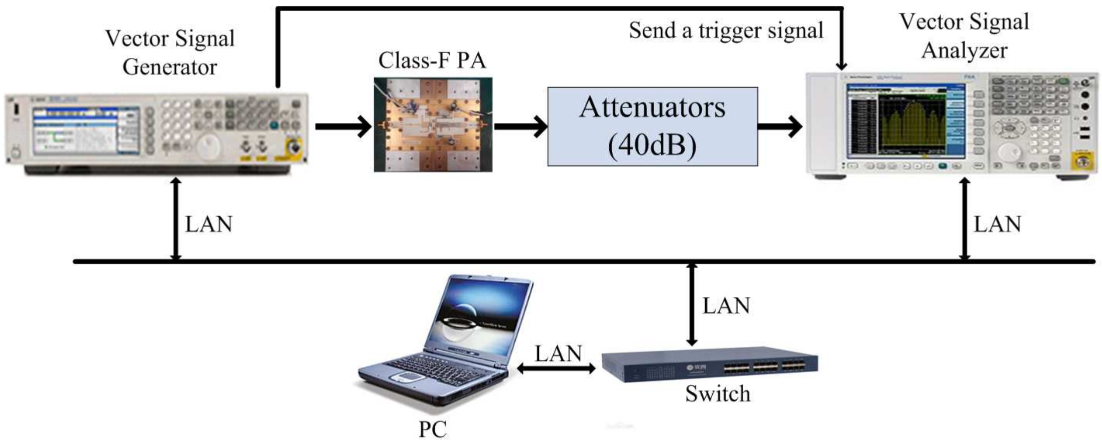

Figure 1. Experiment test bench.

down-converted and demodulated using N9030A. We select a single carrier 16 quadrature amplitude modulation (QAM) signal with 20 MHz bandwidth as the input. The models are identified based on the indirect learning architecture [5] with the least-square method.

3.1. Forward Modeling Results

Table 2 gives the forward modeling performance. In this table, the model dimensions, normalized mean square error (NMSE) and number of coefficients are reported. From this table, we can see that the NMSE of the GMP model is −42.33 dB, while we note that the NMSE of the MGMP model is −41.91 dB, and the NMSE of the MP model is −39.78 dB. Compared to the MP model, the MGMP model shows a NMSE improvement of 2.13 dB with almost identical number of model coefficients. In comparison with GMP model, the MGMP model acquires considerable forward modeling results, but the number of the MGMP model coefficients decreases 40% more than the GMP model.

3.2. Linearization Performance

Table 3 shows the linearization performance for the single carrier 16QAM signal and 4-carrier WCDMA 1001 signal. Compared to the MP model, the proposed MGMP model shows significant ACPR improvements of 2.33/1.99 dB and 2.62/2.11 dB for the two test signals, respectively with almost identical number of model coefficients. In comparison with GMP model, the MGMP model acquires considerable linearization performance, but the number of the MGMP model coefficients reduces 40% more than the GMP model.

Figure 2 shows the spectrum performance before and after DPD when using the MP model, GMP model and MPGMP model for the single 16 QAM signal when the PA average output power is 35 dBm.

Table 2. Forward modeling results.

Model	Model dimensions	NMSE (dB)	Number of model coefficients
MP	$(K, M) = (9, 5)$	−39.78	30^a
GMP	$(K_a, M_a) = (7, 4)$, $(K_b, M_b, L_b) = (5, 3, 2)$ $(K_c, M_c, L_c) = (5, 3, 2)$	−42.33	52^b
MGMP	$(K_a, M_a) = (7, 4)$, $(K_b, M_b, L_b) = (5, 3, 2)$ $(K_c, M_c, L_c) = (5, 3, 2)$	−41.91	31^c

Table 3. Linearization performance for single 16QAM signal and WCDMA 1001 signal.

DPD approaches	single 16QAM signal		WCDMA 1001 signal		Number. of model coefficients
	ACPR of lower band (dBc)	ACPR of upper band (dBc)	ACPR of lower band (dBc)	ACPR of upper band (dBc)	
DPD OFF	−36.31	−34.79	−34.93	−34.17	/
DPD MP	−48.12	47.37	−47.78	−47.74	30^a
DPD GMP	−50.77	−49.89	−50.47	−50.17	52^b
DPD MGMP	−50.45	−49.36	−50.40	−49.85	31^c

[a] $(9+1)\times(5+1)/2 = 30$

[b] $(7+1)\times(4+1)/2+(5-1)\times(3+1)\times 2/2+(5-1)\times(3+1)\times 2/2 = 52$

[c] $(7+1)\times(7+3)/8+4-(7-1)/2+[(5-1)\times(5+1)/8+3-(5-3)/2]\times 2+[(5-1)\times(5+1)/8+3-(5-3)/2]\times 2 = 31$

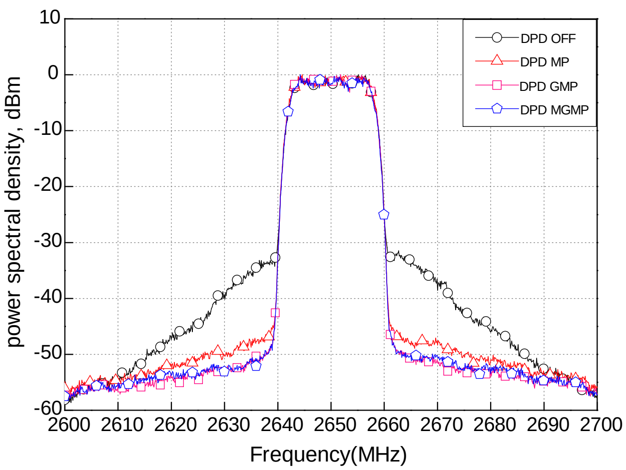

Figure 2. Spectral performance for single carrier 16QAM signal test, when using MP GMP and MGMP DPDS.

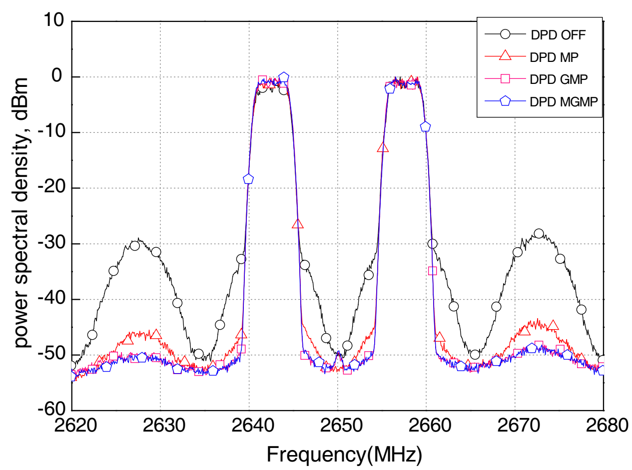

Figure 3. Spectral performance for WCDMA 1001 signal test, when using MP, GMP and MGMP DPDS.

Fig. 3 shows the spectrum performance before and after DPD when using the MP model, GMP model and MPGMP model for the WCDMA 1001 signal when the PA average output is 32 dBm. It is obvious that both the MGMP model and GMP model can realize better linearization effectiveness of PA than the MP model, while the MGMP model achieves comparable accuracy compared to the GMP model in suppressing spectral.

4. CONCLUSION

In this paper, a modified generalized memory polynomial model is proposed for behavioral modeling and DPD of RF PAs. It applies complexity-reduced technique to generalized memory polynomial model. Experimental results including forward modeling results and linearization performance show that the MGMP model outperforms the MP model and GMP model, integrating both model accuracy and complexity.

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